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Linking investment spikes and productivity growth

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Abstract We investigate the relationship between productivity growth and investment spikes using Census Bureau's plant-level dataset for the U.S. food manufacturing industry. There are differences in productivity growth and investment spike patterns across different sub-industries and food manufacturing industry in general. Our study finds empirical support for the learning-by-doing hypothesis by identifying some cases where the impact of investment spikes on TFP growth presents a U-shaped investment age–productivity growth pattern. However, efficiency and the learning period associated with investment spikes differ among plants across industries. The most pronounced impact of investment age on productivity growth (5.3 % for meat products, 4% for dairy products, and 2.8 % in all food manufacturing plants) occurs during the fifth year of post-investment spike. Thus, in general, the productivity gains tend to be fully realized with a 5-year technology learning period for this industry.

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1 Introduction

Investment's role in stimulating growth is central to the evaluation (or initiation) of government policies, such as investment tax credits, which is based on the assumption that investment creates higher productivity. The theoretical models of technological adoption provide some insight into the relationship between investment, technology, and productivity. One common insight from these models is that a period of adjustment exists after a new technology is adopted,[1] where production units engage in technology-specific learning (Parente 1994; Klenow 1998; Yorukoglu 1998). This implication aligns with Jovanovic and Nyarko (1996)'s learning-by-doing model where productivity can be lower than under the old technology after a new technological introduction but productivity then increases as the firm learns how to use the new technology. The installation of a new technology in a plant's production process may create operational inefficiency in the early stages of a new technology, since new skills and experience need to be developed. This may lead to a drop in total factor productivity (TFP) immediately after the introduction of new technology, but in later periods, plants and firms can expect a gradual recovery.

The empirical evidence of the link between productivity and investment remains unclear and the literature's findings are partitioned into two categories. Studies such as Power (1998) examine the link between investment and productivity empirically at the plant level in the U.S. manufacturing industries and find no observable relationship between labor productivity and investments. On the other hand, Sakellaris (2004) and Huggett and Ospina (2001) find that lumpy investment episodes result in the costly adoption of new technologies that involve new equipment leads to TFP falling after the investment spike and starting to recover slowly in the US and Columbian manufacturing plants, respectively. Bessen (1999) also finds that new plant productivity improves as a result of learning-by-doing and indicates that new plant adjustment is not entirely the same as mature plant adjustment after an investment spike; in particular, the large new plant lowers its workforce as it grows older.

The production units such as firms or plants make purchases which increase their real capital stocks by more than a critical fraction are considered to be adopting a new technology which is embodied in the new equipment (Huggett and Ospina 2001). This process is supported by the findings of plant-level studies where a large portion of investments at the plant level is concentrated in a few investment episodes (Doms and Dunne 1998; Cooper et al. 1999; Nilsen and Schiantarelli 2003). However, the investments that production units undertake at the plant level can be in different types

[1] Cooley et al. (1997) argue that new machinery embodies the latest technology, and studies such as Greenwood et al. (1997), De Long and Summers (1991) and Huggett and Ospina (2001) consider an equipment purchase as a mechanism to adopt a new technology.

(e.g., expansionary, replacement, and retooling types of investments) and different investment types may lead different productivity outcomes. For example, if a production unit's investment is a replacement (restoring depreciated capital with new capital) or retooling (equipment purchases reflecting technology adoption) types, one would expect an increase in productivity of these plants after these types of investments[2]; on the other hand, if investment is of an expansionary type (reflecting the acquisition of more capital of a technology known to the plant), then we would expect no change in productivity after such an investment.

In the absence of a unifying theory relating investment spikes to productivity growth, we undertake an empirical investigation into the link between investment spikes and productivity growth by specifically identifying investment spikes through plants' lumpy capital investments and measuring TFP growth around such events.[3] The aim of this article is two-fold: the first is to provide a basic description and unbiased measurement of TFP growth, based on the industry average and quartile grouping of plants' productivity growth, to examine if there are wide productivity differences across plants; the second is to investigate the empirical link between productivity growth and large investments, and examine how productivity growth changes in the presence of lumpy investments and the potential impact of learning-by-doing.

This study contributes to the literature in several ways. We find empirical evidence of a link between productivity growth and investment when we look closely at the most micro production unit—plant level—for one manufacturing industry instead of pooling all industries together into a common technology. This allows us to investigate the productivity–investment relationship in a more detailed manner by dividing the plants into TFP quartile groups and assess the differences in this relationship among high, medium (or middle quartiles) and low productivity growth plants. This reveals an interesting relationship between investment spikes and productivity growth which is masked in studies using a general pooled-industry base. Further, this study finds empirical support for the learning-by-doing hypothesis by identifying some cases where TFP growth drops immediately after the investment episodes, and then starts to recover. However, our study emphasizes the importance of the investment types in supporting the learning-by-doing hypothesis: due to different investment types, different productivity outcomes are observed after plants' lumpy investment events.

The article is organized as follows. The next section introduces the data sources and a description of the dataset. This is followed by an introduction of the methodological and empirical specification which involves TFP growth estimates that are purged of possible endogeneity when using a production function that account for plant heterogeneity. The final section offers some concluding comments.

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[2] Generally retooling type of investments is considered as adopting better technology or major advances in technology, and therefore, when a production unit invested in retooling type, it is expected to have long lasting increase in its productivity. And since the replacement investment is generally restoring depreciated capital with the new capital, this may result an immediate boost in productivity and then a decline in productivity afterwards.

[3] Investment spikes are defined typically as an absolute spike when the investment rate exceed 20 % and as a relative spike when the investment rate exceeds the median investment rate by a factor which is typically set between 1.5 and 3.75 (see Power 1998; Cooper et al. 1999) of each plant.

2 Data sources and lumpiness in capital

We provide micro-evidence on the question of the link between investment and productivity by analyzing confidentially the U.S. food manufacturing plant-level data. Focusing on the U.S. food manufacturing industry is a good empirical application to test this relationship for two reasons. First, previous studies mostly focus on all manufacturing industries by pooling all plants together. We see a value of analyzing one particular sector in depth would give us an insight of the link between lumpy investment and productivity changes. By focusing on only one industry, we have the advantage to control better for unobserved heterogeneity across sectors compared to studies which pool all industries together. If these unobserved characteristics of industries cannot be well controlled, then it will be harder to separate the effect of investment spikes on productivity. Second, the U.S. food processing and kindred products industry has been responsive to new technologies in processing, packaging, and marketing of food product and has become increasingly high-tech over the past few decades (Morrison 1997). The industry is a significant sector accounting for about one-sixth of the U.S. manufacturing sector's activity, and it has experienced significant reorganization through mergers and acquisitions. In the industry, manufacturers attempt to increase sales, profits, and market share through consolidation, industrialization, expanding exports, foreign growth, and new value-added product development (Harris 2002). The food and kindred products industry ranks sixth with respect to number of plants among the 20 operating manufacturing industries in the U.S. and produces nearly 14% of the total value of output in the manufacturing sector. Third, the plants in the industry present a lumpy nature of investments which makes this industry a good candidate to investigate the link between these spikes and productivity changes. The nature of lumpy investments in the industry provides insight into the timing of capital investments and to assess if plant productivity falls after a large investment project.

2.1 Data sources

We use annual plant-level data from the Census Bureau's Longitudinal Research Database (LRD). The LRD is a panel that contains detailed plant-level information from the Annual Survey of Manufacturers (ASM) and Census of Manufacturers (CM) of all the U.S. manufacturing industries.[4]

The balanced panel of plants in the Food and Kindred Products Industry (SIC = 20) focuses mostly on the large manufacturing plants over the time period 1972–1995.[5,6]

[4] The CM, which is conducted every 5 years, samples every U.S. manufacturing plant. The ASM continuously samples plants with more than 250 employees. Continuous data exist for large plants and for small plants that are selected to be part of the ASM panel. Small plants have missing information for all years except CM, and ASM panel years if the plant is selected to be part of an ASM; therefore, comprehensive time series information on small plants is not available.

[5] This is the latest available data which was granted from Census Bureau for the purpose of this study. We used the 4-digit Bartelsman-Gray industry deflators from NBER-CES manufacturing database to get the real variables (Bartelsman and Gray 1996).

[6] Entry and exit behaviors of plants during each CM period is available for this sample. We define an entrant as an establishment that was not operating in the previous census ($t-5$) but is operating

Table 1 Number of observations and plants by sub-industries and all food industry plants together

Three digit sub-industries[a]	Meat products (SIC = 201)	Dairy products (SIC = 202)
Number of plants	204	163
Number of observations	4,722	3,775
Percent of total plants	16	13
Machinery investments of the total industry's machinery investments (%)	10.4	6.1
Building investments of the total industry's buildings investments (%)	15.6	7.2
Combined machinery and building investments of the total industry's combined machinery and building investments (%)	11.4	6.3
Material expenditure of the total industry's material expenditures (%)	28.6	11.2
Energy expenditure of the total industry's energy expenditures (%)	13.3	7.3
Labor expenditure of the total industry's labor expenditures (%)	25.2	6.1
Total value of shipments of the industry's total value of shipments (%)	21.1	9.3
Average employment of the total industry's employment (%)	19	5.5

[a] There are 1,233 plants and 29,592 observations in all Food Industries (SIC = 20).

The balanced nature of the dataset ensures that the capital stocks are constructed using the perpetual inventory method and the lumpiness of investment is measured through time.[7] The balanced panel is not a random sample of plants and includes a higher proportion of large plants due to the ASM sampling strategy. Approximately one-third of ASM sample is rotated in and out of the sample every 5 years to minimize the reporting burden on small plants.

Footnote 6 continued
in the current census (t). Similarly, we define an exiting plant as an establishment that was operating in the previous census ($t-5$), but it is not operating in the current census (t). Our results show that 15 % of plants enter to and 17.9 % of plants exit from the food industry between 1972 and 1977. Similarly, 11.5 % (19.3 %), 11.7 % (14.1 %) and 12.9 % (12.5 %) of plants enter to (exit from) the food industry during 1977–1982, 1982–1987 and 1987–1992, respectively. In these periods, although a higher percentage of plants exited from the industry, total market share of the entrants is higher than that of the exiting plants except during 1982–1987. In general, our results indicate that entrants play an important role in the food industry.

7 We focus on the balanced panel to minimize the measurement error in TFP growth calculation and the difficult measurement issues for capital variable in the unbalanced panel setting. Other studies which face similar capital measurement difficulties use balanced panel (Caballero et al. 1995; Cooper et al. 1999; Cooper and Haltiwanger 2006).

We also analyze two of the major sub-industries in the food industry (meat and dairy products) to investigate the differences in results due to the aggregate versus disaggregate nature of the samples. The meat and dairy products sub-industries are selected based on the relative importance and the type of products (homogenous products) among the sub-industries in the food industry. These two sub-industries differ in two important aspects. The first is by the role of government pricing regulation. Where meat products are free from direct government pricing influence, the dairy products sector has the price of raw material (milk) regulated and regulation influencing the pricing of fluid milk prices in some regions through marketing orders. The second aspect is in terms of technology differences between the two sub-industries. The meat products sub-industry prepares a range of products that flow off a common line of production as products are further processed (e.g., cuts of meat processed into lunch meats, sausages). Milk products tend to involve a wide range of different technologies (e.g., cheese-making, yogurt, and ice cream) that have specialized equipment with milk entering in these specific sub-product processes in a fairly unprocessed form. Table 1 presents a general industry overview based on the panel data used in the analysis.

2.2 Lumpiness in capital in the food industry

The studies analyzing the nature of investments at the plant and firm level document irreversibility (zero investment episodes mixed with periods of investment) and lumpiness (bursts of investments are surrounded by periods of low level of investment activity) (Doms and Dunne 1998; Power 1998; Cooper et al. 1999; Nilsen and Schiantarelli 2003). The evidence of lumpy investment can be explained by the presence of fixed costs which can be a result of the differences in capital vintages across firms and plants. The intermittent and lumpy nature of investments creates a non-smooth adjustment path for the capital stock which contrasts the standard neoclassical investment model with convex adjustment costs. Since understanding the nature of capital adjustment cost is important due to its influences on firm's investment decision, studies search for evidence about the shape of the adjustment cost instead of assuming a conventional shape. One of the most recent studies which uses structural model of capital adjustment costs finds that both convex and non-convex elements should be present in modeling adjustment costs (Cooper and Haltiwanger 2006).

To assess the nature of investment patterns, we present main characteristics of the investment rate distribution in our data series. Throughout this study, the ratio of a plant's investments on capital to its real capital stock (I/K) is used as the definition of the investment rate.[8] Capacity-improving investment activity is measured by lumpy investments. The lumpy investments are defined as the relative measure if the plant's investment rate in a given year is greater than 2.5 times the plant's median investment rate. Since we measure lumpiness for the plants that are in the meat products sub-industry, dairy products sub-industry, and the food industry separately, we

[8] This study focuses on expenditures data on capital and does not take into consideration of the capital retirements. This is because LRD contains some data on capital retirements until 1988 which would limit the time frame of our study to late 80s and these data contain some errors (Doms and Dunne 1998).

define lumpy investments for plants as unusually high investment in relation to the *sectoral median investment rate* over the sample period.[9] The detailed study by Power (1994) describes a relative spike as being where the plant's investment is considered lumpy if it is large relative to that plant's other investments.[10]

Table 2 presents the number of spike observations and their contribution to total plant-level investment for machinery, buildings and their sum. In the food industry, only 17 % of the observations present machinery investment spikes, but these account for 84 % of the total investment. A similar pattern is revealed across other industries. Even though the lumpy investment percentage is lower than the non-spike investment percentage across investment types, the percentage of total sample investment accounted for by lumpy investments are significantly higher than those that are not. This suggests that plant-level investment is quite lumpy, since a relatively small percentage of observations account for a disproportionate share of overall investments. Table 3 provides additional interesting information on investment spike concentration and documents the lumpiness of plant-level investment in the sector. It shows the number of investment spikes over a 24-year period and the percentage of plants with spikes across three different food industries.[11] In the food manufacturing industry, 97 % of the plants experience between 1 and 6 machinery investment spikes over the sample period, suggesting that, at most, only 3 % never have lumpy investments. Of those plants engaged in lumpy investments between 1 and 6 times over the sample period, the median number of investment spikes is four.

3 Linking TFP growth to capacity-improving investment

Identifying the relationship between productivity growth and investment is challenging, and previous research has been only partially successful. The major complication arises from the causality between investment and productivity. An investigation into the relationship between lumpy investment and TFP growth can draw on the results of the theoretical studies by Ericson and Pakes (1995) and Pakes and McGuire (1994). Building a model to illustrate how total factor productivity (TFP) growth rates relate to investment rates, Ericson and Pakes (1995) find that the high mortality rate of new firms is associated with an initial learning period where most perform poorly and have low levels of investment after the initial startup costs. There is a threshold of TFP growth rates where firms decrease their investment after passing the threshold. Baumol and Wolfe (1983) anticipated this result as they explore R&D investment feedback effects

[9] For example, we use 0.184, 0.172, and 0.179 median machinery investment rates for plants in the meat products, the dairy products and all food industry plants, respectively. We also tried the absolute spike definition as a robustness check and our results were not strikingly different across definitions.

[10] Power (1994) defines spikes as abnormally high investment episodes relative to the typical investment rate experienced within a plant and considers various hurdles over the median investment rates (such as 1.75, 2.5, and 3.5 times of median investment rate) to reflect abnormally high investment episodes. An excellent extensive investigation of these alternative specifications of investment spikes and their comparisons can be found in this study.

[11] Confidentiality restrictions preclude us to report information for plants which present greater spike episodes than the ones that are reported in this table.

Table 2 Investment spike characteristics in industries across investment types

Industries Investment rate[a]	Meat products industry		Dairy products industry		Food manufacturing industry	
	% of obs. in data set which are spikes and non-spikes	% of total sample investment accounted for by spikes and non-spikes[b]	% of obs. in data set which are spikes and non-spikes	% of total sample investment accounted for by spikes and non-spikes	% of obs. in data set which are spikes and non-spikes	% of total sample investment accounted for by spikes and non-spikes
Machinery	17 spike	84 spike	20 spike	88 spike	17 spike	83 spike
	83 non-spike	16 non-spike	80 non-spike	12 non-spike	83 non-spike	17 non-spike
Buildings	35 spike	97 spike	37 spike	99 spike	35 spike	97 spike
	65 non-spike	3 non-spike	63 non-spike	1 non-spike	65 non-spike	3 non-spike
Combined machinery and buildings	20 spike	87 spike	21 spike	88 spike	19 spike	84 spike
	80 non-spike	13 non-spike	79 non-spike	12 non-spike	81 non-spike	16 non-spike

[a] Relative spike defined as investment rate that exceeds (2.5*median investment rate)
[b] Percent of total sample investment accounted for by spikes is found by the ratio of investment spikes to total investment

Table 3 Number of investment spikes and the percentage of plants in each spike across industries

Spikes	Meat products industry			Dairy products industry			Food manufacturing industry		
	Machinery	Building	Machinery and building combined	Machinery	Building	Machinery and building combined	Machinery	Building	Machinery and building combined
	% of plants	% of plants	% of plants	% of plants	% of plants	% of plants	% of plants	% of plants	% of plants
1	3.92	1.47	3.43	1.227	0.613	0.613	0.406	0.162	0.162
2	4.9	0.98	3.92	4.908	0.613	6.135	7.299	1.217	5.677
3	22.06	2.45	12.26	14.11	3.067	7.362	24.412	2.758	15.896
4	32.84	4.9	25.98	28.834	3.067	20.245	30.495	4.785	28.467
5	23.04	4.9	24.02	28.221	4.908	25.153	24.006	8.921	24.655
6	8.33	12.26	16.67	17.791	12.883	27.607	10.138	9.895	15.491
7		11.77	8.33		10.429	11.043		11.273	7.461
8		12.75			15.951			14.355	
9		18.14			12.883			12.247	
10		10.78			9.202			11.192	
11		7.35			9.816			7.38	
12								5.515	

and productivity growth rates. In our study, the absence of plant-level R&D data precludes the specific empirical identification of the direct relationship between R&D and investment spikes. However, R&D activity is associated with changes in how a firm undertakes its production activities. These changes can involve significant additions and reorganizing of production processing and capacity which involves large changes in capital stock. Initiatives to install additional capital may arise from a need to enhance productivity growth.

We investigate the link between investment spikes and TFP growth without imposing any causal relationship between them by using reduced form regressions. The following sections will focus on the estimation of TFP growth using production function specification and investigate the relationship between TFP growth and lumpy investments for all dairy, meat, and food plants.

3.1 Production function estimation and TFP growth findings

We measure TFP growth through production function estimation. In production function estimation, Marschak and Andrews (1944) raised the problem of simultaneity between unobservable productivity and observable input choices. This simultaneity is a result of the profit-maximizing firms' response to positive productivity shock by expanding output, in turn, using more inputs. Marschak and Andrews (1944) suggested that the transmitted productivity shock would be positively correlated with variable inputs, and the estimated coefficients on variable inputs from least squares are likely to be biased upward (Levinsohn and Petrin 2003). Under this condition, least squares estimates of production functions are biased which leads biased productivity estimates. Olley and Pakes (1996) address the simultaneity problem by using investment as a proxy to control for the part of the error correlated with inputs and thus eliminate the variation which is related with the productivity contribution. However, an investment proxy is only valid for plants reporting non-zero investment. A difficulty arises with the Olley-Pakes approach when adjustment costs are non-convex, which leads the non-responses in investment to some productivity shocks. This is specifically a concern at the plant-level sample where one can come across many zero investments. Levinsohn and Petrin (2003) address the simultaneity problem by using an intermediate input (e.g., materials, fuel, and electricity) as a proxy controlling for the error associated with simultaneity. They argue that these inputs respond more smoothly to productivity shocks and are useful proxies for plant-level studies since they are generally not equal to zero. From the perspective of adjustment costs, it is less costly to adjust the intermediate input implying this input may respond more fully than investment to the entire productivity term. Consequently, the Levinsohn–Petrin approach presents a compelling remedy to the simultaneity problem in the presence of frequent zero investment observations. [12]

[12] A recent review article by Ackerberg et al. (2006) offers a critique of the Olley–Pakes and Levinsohn–Petrin approaches by arguing that labor may also not be optimally selected along with materials in the current period which leads to the coefficient on labor being unidentified. Ackerberg, Caves, and Frazer then develop a mixture of the Olley–Pakes and Levinsohn–Petrin approaches resulting in a Leontief-type component with labor. As a result, labor is only related in a fixed proportion, and its parameter can be

We estimate a Cobb-Douglas production function using this approach with intermediate inputs to address the simultaneity problem. The estimated Cobb-Douglas production function specified in logs as

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_m m_{it} + \beta_l l_{it} + \beta_e e_{it} + \beta_t t + \omega_{it} + \eta_{it} \tag{1}$$

where y_{it} is the log of the output (the total value of shipments is adjusted for inventory changes) for plants i and time t. The log of materials, labor, energy, and capital are represented by m_{it}, l_{it}, e_{it}, and k_{it}, respectively. Capital is constructed using the perpetual inventory measure, which is appropriate in a balanced panel. The inventory measure of capital is accomplished by accumulating investment over time and requires continuous observations for each plant. The productivity impact is represented by the error term, $\omega_{it} + \eta_{it}$, where ω_{it} is a transmitted error term and impacts the firm's decision rules, and η_{it} is an $i.i.d.$ shock not known to the analyst and does not have an impact on the firm's decisions. We use the energy variable as the proxy to control for the error associated with simultaneity and proceed with the estimation by rewriting Eq. (1) as[13]

$$y_{it} = \beta_m m_{it} + \beta_l l_{it} + \beta_t t + \phi_{it}(e_{it}, k_{it}) + \eta_{it} \tag{2}$$

where

$$\phi_{it}(e_{it}, k_{it}) = \beta_0 + \beta_e e_{it} + \beta_k k_{it} + \omega_{it}(e_{it}, k_{it})$$

The demand for the intermediate input, e_{it}, is assumed to depend on the firm's state variables, $e_{it} = e_{it}(\omega_{it}, k_{it})$. Using the Levinsohn–Petrin condition where the energy function is monotonic function with respect to the productivity shock, ω_{it}, the unobservable productivity term can be written as a function of two observed inputs, $\omega_{it} = (e_{it}, k_{it})$. The first stage estimator is linear in variable inputs and non-parametric in ϕ_{it} where we can obtain consistent estimates of freely variable inputs. We employ Levinsohn–Petrin's locally weighted quadratic least squares approximation (least squares with a polynomial approximation approach) to obtain the coefficients of freely variable inputs. In the second stage, since capital and energy variables enter $\phi_{it}(.)$ twice, Levinsohn–Petrin propose two moment conditions to identify β_k and β_e. To identify β_k, they assume that productivity shock is governed by a first-order Markov process, $\omega_t = E[\omega_t|\omega_{t-1}] + \xi_t$ where ξ_t is an innovation to productivity that is uncorrelated

Footnote 12 continued
estimated properly. In the end, the theoretical suitability of the approach depends on the assumptions of the data-generating processes for the application at hand, with the Ackerberg–Caves–Frazer remedy coming at the cost of a major production technology restriction. While Ackerberg et al. (2006) find their estimator appears to be more stable across different proxy variables compared to the Levinsohn–Petrin approach for the same dataset as Levinsohn and Petrin (2003), no practical difference is found using the Olley–Pakes approach for the labor coefficient by Iranzo et al. (2008).

13 We tried material and energy inputs as possible proxy variables in specifying the Levinsohn–Petrin estimation. Based on the characteristics of the data (less nonzero values in energy) and the results from least squares/Levinsohn–Petrin coefficients on variable inputs, we have chosen energy input as a proxy.

Table 4 Coefficient estimates from least squares and Levinsohn and Petrin (LP) approaches across industries

	Meat products industry		Dairy products industry		All food industry	
	OLS	LP	OLS	LP	OLS	LP
Capital	0.0231	0.0700	0.0455	0.0800	0.0735	0.0100
	(0.0061)	(0.0324)	(0.0112)	(0.0321)	(0.0050)	(0.0050)
Labor	0.0741	0.0654	0.1286	0.1123	0.1840	0.1784
	(0.0205)	(0.0197)	(0.0158)	(0.0133)	(0.0080)	(0.0081)
Material	0.7621	0.7563	0.7687	0.7649	0.6532	0.6441
	(0.0208)	(0.0228)	(0.0230)	(0.0219)	(0.0097)	(0.0091)
Energy	0.1259	0.1100	0.0687	0.0900	0.0705	0.1000
	(0.0217)	(0.1268)	(0.0225)	(0.1046)	(0.0089)	(0.0173)

Standard errors are in parentheses. The Wald tests of constant returns to scale from Levinsohn and Petrin (2003) method are as follows; Chi-squared = 0.02 ($p = 0.8949$), Chi-squared = 0.27 ($p = 0.6024$), Chi-squared = 18.71 ($p = 0.0000$) for meat products, dairy products, and all food manufacturing industries, respectively. These results show that meat and dairy product industries have CRTS and all food industry have DRTS

with k_t, $E[(\xi_t + \eta_t)k_t] = E[\xi_t k_t] = 0$ and to identify β_e, they assume that last period's energy choice should be uncorrelated with the innovation in productivity this period, $E[(\xi_t + \eta_t)e_{t-1}] = E[\xi_t e_{t-1}] = 0$.

Table 4 reports coefficient estimates from least squares and Levinsohn–Petrin approaches. We find that parameter estimate on freely variable inputs from the least squares procedure exceed the ones from the Levinsohn–Petrin method which are consistent with the theoretical and empirical results discussed in their article.[14]

We use coefficients from the production function estimation by Levinsohn and Petrin (2003) method to generate productivity growth for each plant and each year, across meat and dairy products as well as all food manufacturing industries.[15]

[14] To see if the least squares coefficient on capital will be biased upward or downward depends on the degree of correlation among inputs and the productivity shocks (Levinsohn and Petrin 2003). They suggest that if capital also responds to the productivity shock, we also see upwardly biased capital coefficient; however, there might be situation when capital is not correlated with the period's transmitted shock (but variable inputs are) or capital is much less weakly correlated with the productivity shock than the variable inputs are—then, the least squares estimate on capital is likely to be biased downward (Levinsohn and Petrin 2003). Our results show that, in meat and dairy industries, the least squares estimate is less than the Levinsohn–Petrin estimate which indicates the least squares coefficient on capital is biased downward, and in the entire food industry, the least squares estimate is higher than the LP estimate which indicates that the least squares coefficient on capital is biased upward.

[15] To generate productivity growth, we use the well-known TFP growth decomposition which comprises the scale and the technical change components as follows, $T\hat{F}P = (\varepsilon - 1)\hat{F} + \hat{A} = \left(\sum_{j=1}^{n} \frac{F_{X_j} X_j}{Y} - 1\right) \sum_{j=1}^{n} \frac{F_{X_j} X_j}{\sum_{i=1}^{n} F_{X_j} X_j} \hat{X}_j + \hat{A}$ where $T\hat{F}P$ refers the productivity growth; $(\varepsilon - 1)\hat{F}$ denotes the scale effect, in which, $\hat{F}$ presents input growth (Y is the output and X_j are the inputs (l, m, e, k) of the plant's production function) and ε presents scale elasticity; and $\hat{A}$ refers the technical change effect.Thus, the productivity growth is generated by means of marginal products from the Levhinson-Petrin regression

Table 5 TFP growth across industries and quartile groups

Quartile	Mean TFP growth in meat	Mean TFP growth in dairy	Mean TFP growth in all food
Lowest (I)	−0.1826	−0.1836	−0.2056
Lower middle (II)	−0.0291	−0.0383	−0.0272
Upper middle (III)	0.0228	0.0094	0.0345
Highest (IV)	0.1905	0.1547	0.2149
All	0.0005	−0.0142	0.0042

Dhrymes (1991) and Bartelsman and Dhrymes (1998) present TFP growth results by deciles and their conclusions argue against characterizing the economy in terms of the representative plant or firm. These studies suggest that evaluating TFP growth patterns by quartiles can potentially reveal differing TFP growth impacts from investment spikes. Thus, similar to Dhrymes (1991) contemporaneous rank procedure which is applied to present TFP growth by deciles, after calculating a given plant's TFP and its growth, we rank all plants according to the magnitudes of their TFP *in each year*. Then for each year, the plants are grouped by a quartile sampling procedure ranging from I to IV (lowest to highest). Thus, we obtain TFP growth of plants in each quartile, per year. This ranking allows us to classify plants exhibiting varying levels of TFP growth, as well as to detect if productivity is growing over time.

Table 5 provides overall and quartile group specific average TFP growth across industries. This shows that the average productivity growth over the years is 0.05 % in meat products, −1.4 % in dairy products and 0.4 % in all food manufacturing industries. However, classifying plants based on their productivity quartiles reveals significant variation in productivity growth. An analysis of the 3-digit sub-industry level presents very different productivity growth rates even when each sub-group belongs to the same 2-digit-level aggregate industry. The meat product plants in the lowest quartile have an average growth of −18 %, while the highest quartile plants are at 19 %. A similar pattern is seen in the dairy products sub-industry and the entire food industry with the average growth in the lowest quartile ranked plants is −18 % for dairy products and −21 % for the food industry, while the average growth in the highest quartile is 15 and 22 %, respectively.

Overall in the U.S. food industry, the smallest- and the largest-sized plants are more productive than the plants that are in the other size categories. Further, the older plants have higher productivity growth compared to the productivity growth of the youngest plants.

These results present several interesting observations about the industry, such that there are large differentials in the rates of productivity growth across plants within the same industry. The industry-level productivity growth presents a different picture than growth based on a quartile plant group. Most interestingly, one expects poorly

Footnote 15 continued
estimation. Since the Cobb-Douglas production technology (with constant returns to scale) is estimated here, the TFP growth is coming from the technical change component.

performing plants to exit over the long run in a competitive environment. These results find low productivity growth plants coexist with the highly productive ones. These differences may be attributed to the quality of capital equipment, worker's skills, or the development and installation of new technology and the managerial abilities of firms explain the wide variation in productivity growth.

3.2 The impact of investment spikes on productivity growth

We describe an econometric model to investigate the link between investment spikes and TFP growth. For this analysis, we use the reduced form regression model as follows,

$$Q_{it} = \alpha + \gamma X_{it} + \varepsilon_{it} \tag{3}$$

where the dependent variable Q_{it} is the productivity growth rate, and the independent variables X_{it} (vector) are relevant plant characteristics (e.g., plant investment age (lagged), plant size, plant age, year and industry controls).[16] The investment age variable measures the time since the plant's most recent investment spike. After identifying investment spikes for each plant over the years, the investment age variable is constructed by measuring the time since the plant's most recent investment spike. Based on our panel from 1972 to 1995, we constructed the investment age dummies. The range of investment age dummies is 0 to 9+, where 0 denotes consecutive spikes, 1 represents a one-year investment spike interval, and so on, up to the nine-or-greater category. The time since the plant's most recent investment spike can also be viewed as an indicator of the plant's capital vintage. The size variable is a set of dummy variables defined as the number of employees at each plant. Plant size dummies are assigned based on their average, size-weighted employment over the sample period to account for each plant's average employment in the long term and to avoid size fluctuation through time. After finding the average size-weighted employment, plant size dummy variables are created based on quartile groups. Table 6 reports the number of observations and plants, average size, and employment based on plant size quartiles. Table 7 presents the number of plants and observations by plant age. The construction of the variables follows the protocol presented in the Appendix of Geylani and Stefanou (2011).

Our empirical estimation only focuses on machinery investment spikes, which are the type of investment that usually incorporates the latest technology. Using Eq. (3), we estimate a set of least-squares regressions with and without fixed effects to exploit both cross-plant and within-plant productivity variations.[17] Table 8 lists the estimation results from Eq. (3) for each industry. We plot the plant investment age coefficients

[16] Our industry dummies are at the 4-digit SIC level, which shows a 4-digit output composition. We have five such industries for Meat and Dairy products, and 51 for the entire food industry.

[17] In plant-level estimation, if there is unobserved heterogeneity across plants, the estimated coefficient using least squares without controlling for the fixed effects yields biased results. Therefore, we run a least squares regression with plant-level fixed effects to eliminate this potential bias.

Table 6 Number of observations and plants, organized by plant size quartile, in the entire food industry

Average size quartiles	Number of observations	Number of plants	Average size by employment index (size variable)	Average size by employment index as % of total average employment index (%)	Average employment
0–25 Quartile group (A)	7,392	308	1754.75	4.4	68.08
25–50 Quartile group (B)	7,392	308	5468.52	13.6	212.39
50–75 Quartile group (C)	7,416	309	9806.55	24.3	379.68
75–100 Quartile group (D)	7,392	308	23255.97	57.7	885.18

Table 7 Number of observations and plants, organized by plant ages, in the entire food industry

Plant age[a]	Number of observations	Number of plants	Fraction in the data set (%)	Average employment
Age 0 (newborn plants in 1972)	4224	176	14	291.53
Age 1 (5-year-old plants in 1972)	2,808	117	9.5	360.10
Age 2 (9-year-old plants in 1972)	22,464	936	76.2	407.57

[a] The first year of panel data, 1972, is taken as a benchmark to find plant age

from columns 2, 4, and 6 in the Table 8 for the meat products, the dairy products, and the food industries in Figs. 1, 2 and 3, respectively.

A major finding from this analysis is the relationship between productivity growth and investment age which is contrary to the findings of Power (1998), and holds even when controlling for plant fixed effects. In general, the magnitude and significance of the investment age coefficients is robust to the presence or absence of plant fixed effects. Therefore, further discussions are based on these results, which control for the unobservable heterogeneity across plants.

The impact of investment age on productivity growth exhibits a positive trend for the meat products industry. This indicates productivity growth increases as a result of an investment spike, which may suggest an efficiency gain or learning effect.[18] For

[18] Investment age coefficients illustrate the relationship between productivity growth and investment age for the average plant relative to the omitted investment age group 9+.

Table 8 Regression results of investment spike effects on TFP growth in the meat products, dairy products and all food manufacturing industries

	Meat products industry		Dairy products industry		All food industry	
	Productivity growth regression without plant fixed effects (1)	Productivity growth regression with plant fixed effects (2)	Productivity growth regression without plant fixed effects (3)	Productivity growth regression with plant fixed effects (4)	Productivity growth regression without plant fixed effects (5)	Productivity growth regression with plant fixed effects (6)
Investment age						
0 years old	0.01174	0.02059	0.00411	0.00714	0.00922**	0.01078**
	(0.01014)	(0.01332)	(0.00964)	(0.01147)	(0.00427)	(0.00519)
1 year old	0.02924***	0.03760***	0.02603***	0.02942***	0.00821*	0.00962**
	(0.00986)	(0.01213)	(0.00963)	(0.01072)	(0.00489)	(0.00489)
2 years old	0.03046***	0.03875***	0.03095***	0.03378***	0.00714*	0.00836*
	(0.00875)	(0.01215)	(0.00793)	(0.01079)	(0.00389)	(0.00492)
3 years old	0.02991***	0.03851***	0.00414	0.00820	0.00068	0.00223
	(0.00856)	(0.01309)	(0.00959)	(0.01153)	(0.00459)	(0.00526)
4 years old	0.04188***	0.04895***	0.03809***	0.04115***	0.00447	0.00575
	(0.01045)	(0.01395)	(0.01073)	(0.01215)	(0.00459)	(0.00554)
5 years old	0.04583***	0.05320***	0.03770***	0.04001***	0.02683***	0.02812***
	(0.01006)	(0.01462)	(0.01192)	(0.01272)	(0.00513)	(0.00576)
6 years old	0.02966**	0.03536**	−0.00344	−0.00138	0.00496	0.00632
	(0.01266)	(0.01526)	(0.01666)	(0.01353)	(0.00585)	(0.00601)
7 years old	0.03077**	0.03628**	0.04217***	0.04406***	0.01475**	0.01583**
	(0.01324)	(0.01559)	(0.01506)	(0.01415)	(0.00595)	(0.00621)
8 years old	0.03843***	0.04371***	0.02194	0.02301	0.01192*	0.01256**
	(0.01244)	(0.01577)	(0.01947)	(0.01482)	(0.00614)	(0.00642)

Table 8 continued

	Meat products industry		Dairy products industry		All food industry	
	Productivity growth regression without plant fixed effects (1)	Productivity growth regression with plant fixed effects (2)	Productivity growth regression without plant fixed effects (3)	Productivity growth regression with plant fixed effects (4)	Productivity growth regression without plant fixed effects (5)	Productivity growth regression with plant fixed effects (6)
Plant age						
Age0	−0.00094	X	−0.00176	X	0.00203	X
	(0.00382)		(0.00292)		(0.00173)	
Age1	0.00887	X	−0.00262	X	-0.00321	X
	(0.00894)		(0.00464)		(0.00228)	
Plant size						
Medium	−0.00337	0.03945	−0.00389	−0.10798	−0.00225	X
	(0.00513)	(0.08746)	(0.00308)	(0.08327)	(0.00162)	
Medium-Large	0.00591	0.10542	−0.00587*	−0.08844	−0.00386**	X
	(0.00617)	(0.11406)	(0.00355)	(0.10637)	(0.00182)	
Largest	0.01032*	0.10313	0.00203	−0.02672	0.00199	X
	(0.00541)	(0.15239)	(0.00341)	(0.12148)	(0.00202)	
N	4,484	4,484	3,581	3,581	28,190	28,190

Coefficients from fixed effect and without fixed effect regressions are reported. Robust standard errors are in parenthesis. Each regression includes year and 4-digit SIC industry controls. The omitted categories are as follows: investment age 9+, the oldest plant age category, the smallest size category, the first year, SIC=2017 (Poultry and Egg Processing 4-digit sub-industry) for Meat Products Industry, SIC=2021 (Creamery Butter 4-digit sub-industry) for the Dairy Products Industry and SIC=2011(Meat Packing sub-industry) for the All Food Manufacturing Industry. ***, **, and * represent 1, 5, and 10% significance, respectively. X represents variables that are dropped from the fixed effect regression

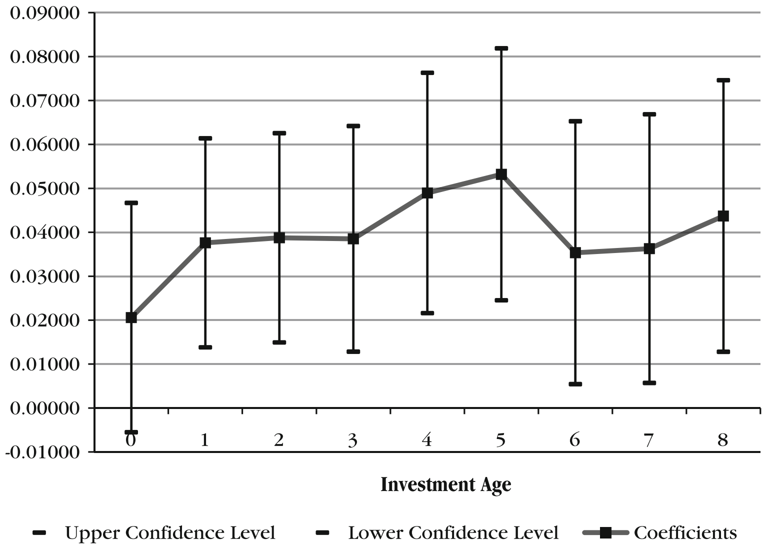

Fig. 1 Investment age and productivity: meat products industry

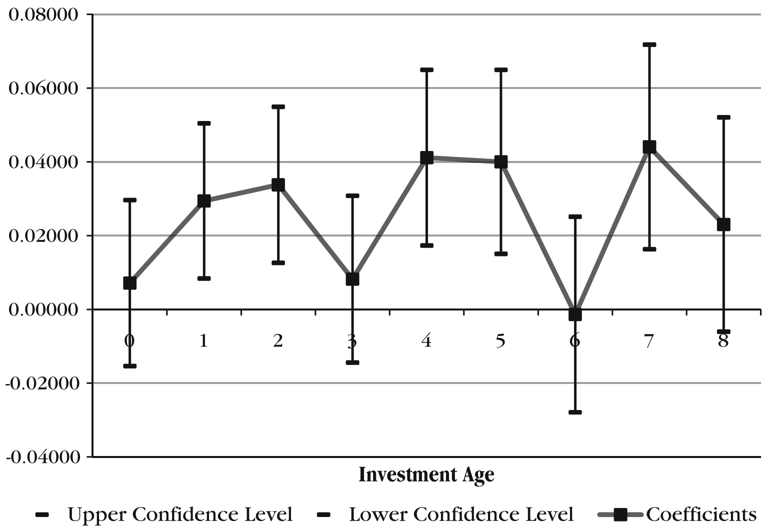

Fig. 2 Investment age and productivity: dairy products industry

example, the impact of that investment for the meat products plants is a 4 % productivity increase 1 year after the investment spike, and increasing to 5 % 4 years after the spike. The pattern is an inverted U-shape, suggesting that productivity growth initially increases and then trails off (Fig. 1). The impact of investment age on productivity growth becomes relatively flat after 1 year suggesting a rapid efficiency gain and/or learning effect. Once the plants adopt the new capacity, it either increases efficiency right away, or the technology learning period is not long, so that plants see the positive effect of this technology on productivity right away.

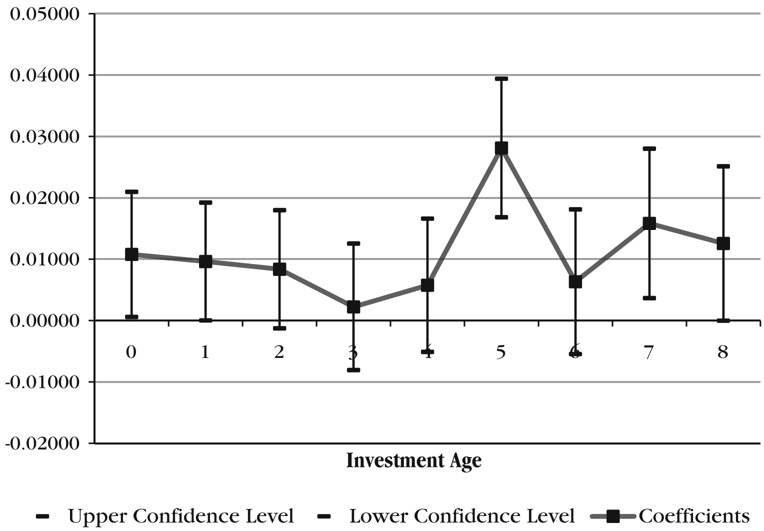

Fig. 3 Investment age and productivity: food manufacturing industry

The positive and significant effect of investment age on productivity growth may indicate that plants in meat products industry may be introducing new technologies to boost their productivity. Thus, these investments may be a replacement or retooling type of investment. The idea that different types of investments (such as expansionary, replacement, or retooling) have an effect on productivity shows up in previous research, but this has never been tested since there were no data available distinguishing investment types precisely enough (Power 1998; Huggett and Ospina 2001; Sakellaris 2004). The Power (1998) study could not find a relationship between productivity growth and investment. This was attributed to the expansionary investment type, which need not be associated with productivity increases. An increase in productivity is expected when there is replacement or retooling type of investment. While our data do not distinguish between investment types, our results can be used to suggest different types of investments in the food manufacturing industry.

For dairy product plants in general, the impact of large investments on productivity growth is positive and is realized after the first year. For example, the impact of that investment for dairy products plants is a 3 % productivity increase 1 year after the investment spike. For these plants, the trend is generally positive, even though some coefficients are insignificant (Fig. 2). While this pattern is very similar to meat product plants, the investment age impact in dairy product plants is about half the rate found in meat plants. Some of the observed differences in the analysis of the large investments impact on productivity growth across meat and dairy plants might be a result of technological and product differences that we see in these sectors.[19]

[19] Meat products plants can offer a range of products based on how the processing is managed. For example, boxed beef products (e.g., pre-processed choice cuts being shrink wrapped and boxed for delivery to retailers) are new products developed over this period which required specialized handling but did not require significant specialized capital. Dairy products can involve sophisticated technologies that require

For the food industry, in aggregate, the most pronounced impact of investment age on productivity growth (2.8 %) occurs during the fifth year after an investment spike. For these plants, the impact of investment age on productivity declines gradually up to investment age 4, then increases during investment ages 4 and 5 (U-shape investment age-productivity pattern). We see this pattern for the food manufacturing plants in Fig. 3. Large spikes generally require significant plant-level learning, and as a result, the pronounce impact of investment spikes appears in later periods, and the productivity benefits from investment are realized more slowly. The learning period is longer for these plants compared to plants observed in the meat and dairy products industries. The U-shape investment age-productivity pattern is consistent with the Jovanovic and Nyarko (1996) learning-by-doing model in which productivity increases as firms learn more about the given technology, implying that when plants abandon an old technology in favor of one that is new, there is a period of technology-specific learning and productivity can be lower immediately after switching to a new technology. Theoretical studies such as Klenow (1998), Yorukoglu (1998), and vintage human capital models of Parente (1994) exhibit similar behavior. More recently, the machine replacement problem (e.g., Cooley et al. 1997; Cooper et al. 1999) which considers technological progress is investment specific and embodied in the form of new capital goods. These models explain the plant-level investment patterns and lumpy investments and are consistent with the findings of this article. Further, our results show that different learning curves (learning period of technology) can exist among different plants in the industry. For example, while we observe longer learning period for the plants in the food industry, in general (U-shape investment age–productivity pattern), we observe a rapid learning curve for the meat and dairy products plants in the food industry (almost an inverted U-shape). This finding is consistent with Greenwood and Jovanovic (2001)'s learning curve model which implies a steeper learning curves for plants during the times of rapid technological progress.[20]

Across all food industries, the most pronounced impact of investment age on productivity growth (5.3 % for meat products, 4 % for dairy products, and 2.8 % in all food manufacturing plants) occurs during the fifth year post-investment spike. Thus, the productivity gains tend to be fully realized with a 5-year technology learning period for this industry.

4 Concluding comments

The main aim of this study is to examine empirically the widely assumed relationship between productivity and investment spikes by means of a rich plant-level dataset, and we investigate this link without imposing any causal relationship between productivity growth and investment for the U.S. food manufacturing industry.

Footnote 19 continued
specialized equipment. For example, the emergence and growth of yogurt products are new dairy products developed over this period which did require specialized processes and equipment.

[20] Other studies which present the literature on learning curves and whose findings are consistent with ours are Argote and Epple (1990) and Bahk and Gort (1993).

This study offers several key results. First, there is a significant variation in productivity growth among plants in the same industry. Productivity growth at the industry level is different from growth measurement based on a quartile group of plants. Second, we find strong evidence of a link between productivity growth and investment age in existing plants. Our results show that productivity growth increases after investment spikes over time and then trails off, even after controlling for plant fixed effects in most of the plants, suggesting a plant-level efficiency gain or learning effect. However, we find that there are differences in productivity growth and investment spike patterns across different sub-industries and the food manufacturing industry in general.

We also find that efficiency and the learning period associated with investment spikes differs across industries. The meat and dairy industry plants see the positive effects right away once the new technology is adopted. This suggests that these plants experience an immediate increase in efficiency, or the new technology learning period is relatively short. However, for the all food industry plants in general, the impact of investment spike on productivity growth is positive but gradually declines after an investment spike, which suggests that the learning period is longer and productivity benefits from these investments are realized more slowly. By focusing on existing plants, this study reveals that lumpy investments not only occur at new plants as most of the existing studies emphasize, but also at surviving plants. This result coincides with the Huggett and Ospina (2001) investigation of Columbian plants.

The natural next step is to focus more deeply on the unobserved heterogeneity of firms to investigate how plant-level investment spikes and productivity growth are linked. This involves a dynamic theory of firm capital adjustment and a structural modeling framework to link different types of investments (e.g., expansionary, replacement or retooling) to different innovation types (process versus product innovation). The pace of firms to absorb the large scale investments is at issue as well as the duration of the installation and overall adjustment of these investments.

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